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SIMULATION FOR EVALUATING LONG-TERM MAINTENANCE PLANS FOR COMPLEX SYSTEMS

Dr. Luke A. Rhodes-Leader

Department of Management Science
Lancaster University
l.rhodes-leader@lancaster.ac.uk

Dr. David J. Worthington

Department of Management Science
Lancaster University
d.worthington@lancaster.ac.uk

Ian Griffiths

Decision Lab Ltd
V.301 Vox Studios, 1-45 Durham Street
London, SE11 5JH
ian.griffiths@decisionlab.co.uk

Panagiotis Samartzis

Decision Lab Ltd
V.301 Vox Studios, 1-45 Durham Street
London, SE11 5JH
panagiotis.samartzis@decisionlab.co.uk

ABSTRACT

The optimisation of maintenance plans for complex systems involving many components is not an easy problem. Analytical and mathematical models are possible, but often need to make significant assumptions and are unable to look at the distribution of costs and failures. This paper discusses a project in which a discrete-time simulation model was added onto an existing optimisation model in order to go beyond just estimating the mean performance and give a better picture of the risk and variability involved with potential maintenance plans.

1 INTRODUCTION

The scheduling of maintenance for complex systems of assets involving many components can be a very challenging problem. The aim is to produce a schedule of when and how to preventively maintain each asset that balances the cost of the scheduled maintenance with the expected cost due to failure within the system. The schedule may be intended for a long planning horizon, often up to 20 years. For large organisations, there can be thousands of assets, with maintenance costs measured in tens of millions of pounds. Furthermore, many assets are dependent structures, made up of heterogeneous components combined in a multi-layered hierarchy, each with their own specific maintenance needs. The structural combinations can be linked in series, parallel or k-out-of-N subsystems. There are often limited budgets on cost and/or manpower that constrain the amount of maintenance that can be performed in a given time window. Thus, the size and structure make maintenance schedule optimisation a complex problem, and the uncertainty in the usable life of each component introduces stochasticity as well.

One approach to maintenance optimisation is using analytical approaches based on stochastic processes (such as Markov chains) and renewal theory (Scarf 1997). These can be very powerful tools, allowing the probabilistic nature of the system to be modelled, but are only tractable for systems with a few components or many identical components (de Smidt-Destombes et al. 2007). This is certainly not the case in many real-life settings. For more realistic cases, the analytical approaches can only be used to motivate heuristic policies.

An alternative is to develop optimisation models, such as Mixed Integer Linear Programmes (MILPs) or Stochastic Programmes (Zhu et al. 2021), that utilise statistical models for the lifetime of components to estimate the risk of failure. Decision Lab have developed such a model, included in their Combined Health Asset Risk Model (CHARM). CHARM is based on an earlier model called CONCEPT, developed for the Canal and River Trust, which was a runner-up in the President's medal OR60 in 2018 (Griffiths and Wilson 2019). These models are much better suited to solving resource constrained problems than the stochastic models. However, in complex hierarchical structures, converting the probabilities of failure for each component into the probability of the asset failing is non-trivial, with approximations often required. And whilst the probabilities include some aspects of stochasticity, the output of the models cannot generate information beyond the mean costs over the time-horizon.

To help overcome the issues associated with stochastic modelling and optimisation models, simulation has been used to test the solutions proposed by those models, such as the work of Barata et al. (2002). Simulation can handle both the complexity and stochastic elements, and enable a full evaluation of a policy with fewer simplifying assumptions. Much of the literature focus on estimating the expected values of cost or lifetime. This is a risk neutral approach and does not take full advantage of simulation to empirically estimate the distribution of these quantities for more informed decision making.

In this paper, we discuss a project that aimed to add simulation to the CHARM tool built by Decision Lab. This multi-fidelity modelling approach enables the plans generated by a MILP to be tested more thoroughly, providing estimates for characteristics of the total maintenance cost distribution (such as the 95$^{\text{th}}$ percentile) and the availability of machines that function in parallel.

One of the key aims was to build a simulation model that could be generalised to the various contexts in which Decision Lab use this type of modelling without the need for significant modification. The model needed to be able to take the input data for CHARM and the optimised maintenance schedule and construct the hierarchical structure of the assets. For this reason, the simulation was built to be as generic as possible.

The rest of this paper is organised as follows. Section 2 gives a brief review of some of the literature on asset maintenance, particularly mentioning examples which feature simulation. The proposed simulation model is described in Section 3, with a discussion on methods for sensitivity analysis in Section 4. In Section 5 we demonstrate the model and its insights on a realistic randomised asset structure, before concluding in Section 6.

2 LITERATURE REVIEW

There is a large literature on maintenance optimisation, covering many methods from Markov decision processes (Olde Keizer et al. 2016) to stochastic programming approaches (Zhu et al. 2021). Here we focus on papers where simulation has played a significant role. For a recent and thorough review of the other areas of the maintenance optimisation literature, we direct readers to the work of de Jonge and Scarf (2020).

Simulation has been applied widely within the optimal maintenance literature. Its usage largely falls into two categories. The first is to evaluate the performance of maintenance policies derived from simplified analytical models. For example, de Smidt-Destombes et al. (2007) consider multiple large k-out-of-N homogeneous systems which all share spare parts and a repair shop. The solution methodology is based on approximating queueing behaviour, and applied to a problem with systems of up to $N = 3000$ components. A discrete-event simulation model is used to evaluate the accuracy of the approximate models. Wu et al. (2016) consider the multi-component case where preventive maintenance is only carried out when a component fails. They propose an importance measure to decide which components to maintain and evaluate this policy with a simulation model. These papers use simulation as an experimental paradigm, whereas in this paper seeks to use simulation as part of the decision making process.

The second use of simulation is as the primary modelling paradigm, and several frameworks have been suggested. Barata et al. (2002) considered condition-based maintenance with constant monitoring of components. They produced a discrete-time simulation model that modelled failure due to both deterioration and random shocks, and also allowed for random improvements from preventive maintenance. Zhou et al. (2015) consider a similar problem to Wu et al. (2016). However, they include planned preventive maintenance as well, and their analysis uses a simulation model to find the optimal policy. Both Barata et al. (2002) and Zhou et al. (2015) use simulation as part of a grid search optimisation. Huseby and Natvig (2013) utilise a Discrete Event Simulation (DES) model to estimate multiple importance measures for network flow systems. Hong et al. (2014) model the degradation of components for condition-based maintenance using Gamma processes. For multiple components that cannot be treated independently, Gamma processes can be analytically intractable, so the authors simulate these systems in discrete time to find optimal inspection periods, focusing on systems in which the degradation of components is dependent. Each of these models target a specific type of maintenance policy, whether condition based or time based. Our simulation is more flexible to evaluate alternative or mixtures of policies.

Chiacchio et al. (2020) developed a framework for simulating systems in which the physical and state environment can alter the lifetime distributions of the components, as well as complex structural dependence, such as spare parts that can also deteriorate when not being used. Their hybrid simulation model uses continuous-time simulation to model the physical system evolution alongside DES mechanisms for more basic failure and repair processes. This complexity leads to significant computational costs. The authors also acknowledge that in many situations, the more complicated behaviour is not known, but that this need not be included within their modelling framework. The simulation model described here uses a similar mechanism of combining DES and time-driven simulation, but not with the aim of modelling the physically processes directly. The time steps are larger influenced by the failure processes we seek to model and reducing computational cost. Another example of a hybrid simulation model for maintenance planning is Mulyana et al. (2020), who apply a combination of Monte Carlo simulation and Systems Dynamics simulation for periodic preventative maintenance for the packing department of a flour mill.

Beyond the maintenance planning discussed in this paper, simulation can also be used directly within the joint optimisation of maintenance and other considerations. Wakiru et al. (2019) use a DES model and simulation optimisation to find good policies involving maintenance and management of the spare-parts inventory. Zahedi-Hosseini et al. (2017) solve a similar problem, testing out various inventory control policies. In both cases, the optimisation is performed over a few variables using a commercial heuristic. Bouslah et al. (2018) focus on a two machine manufacturing line, considering maintenance, production and quality as an integrated problem, with dependent reliability and quality deterioration. The model combines continuous-time simulation and DES. The simulation optimisation uses a Response-Surface Methodology approach. Assid et al. (2015) also look at the joint preventive maintenance and production problem in manufacturing, but in this case examining a single machine that can create two products. The simulation is a hybrid between continuous-time simulation and DES. Similarly, the optimisation is formulated with policy parameters as the decision variables and is solved using a one-step Response Surface Methodology.

3 SIMULATION MODELLING STRUCTURE

Consider an asset constructed from a collection of components. Groups of components form subsystems, which can operate in series (one component failure breaks the subsystem), in parallel (all components must fail to break the subsystem) or in a k-out-of-N structure ($N-k+1$ component failures break the subsystem). Groups of subsystems form Level 1 items in similar structures. (More complex systems may have more levels.) Groups of Level 1 items make up the asset. This structure forms a hierarchical Reliability Block Diagram dictating the reliability behaviour of the asset.

As an example, consider an asset system called Emergency Vehicles. Figure 1 shows part of the reliability block diagram. This asset system is made up of Level 1 items such as Fire Engines and Pumping Systems. In turn, the Fire Engines and Pumping Systems (Level 1 items) are decomposed further into subsystems or components. For example, each Pumping System instance includes two Hose components, which are connected in parallel. In this case, if one Hose breaks down, the Pumping System can still function. Each Fire Engine contains one Camshaft and one Exhaust Manifold as its components and they are connected in series. If either the Camshaft or the Exhaust Manifold fails, the whole Fire Engine they belong to becomes unavailable.

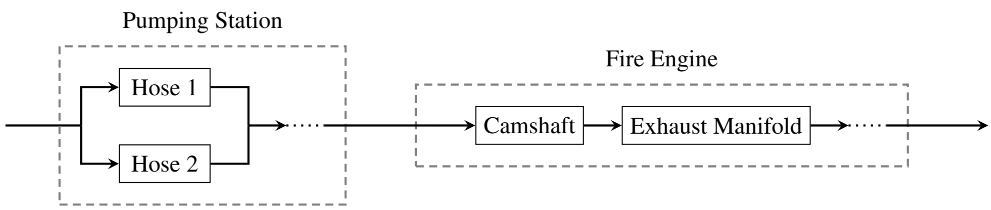

Figure 1: Part of the reliability block diagram of the Emergency Vehicles asset system.

The aim of the model is to simulate the evolution of the asset including its (planned and unplanned) maintenance over the time horizon. Overall, it is the reliability of the asset and the cost of the proposed maintenance interventions schedule that we wish to estimate.

3.1 Model Content

The model used here is a discrete-time simulation written in Python, and utilises the agent-based modelling package MESA (Kazil et al. 2020). We simulate at the component level over a fixed time horizon. Each component is modelled using the 'agent' class of MESA, though little interaction occurs between the components. At each time-step, the component's state (consisting of its age and/or health score, its status (functioning or failed), and accumulated planned and unplanned maintenance costs) is updated. Figure 2 shows the logical steps of each agent update. The information on which components have failed and the Reliability Block Diagram structure is then used to calculate whether the system has failed and any associated costs.

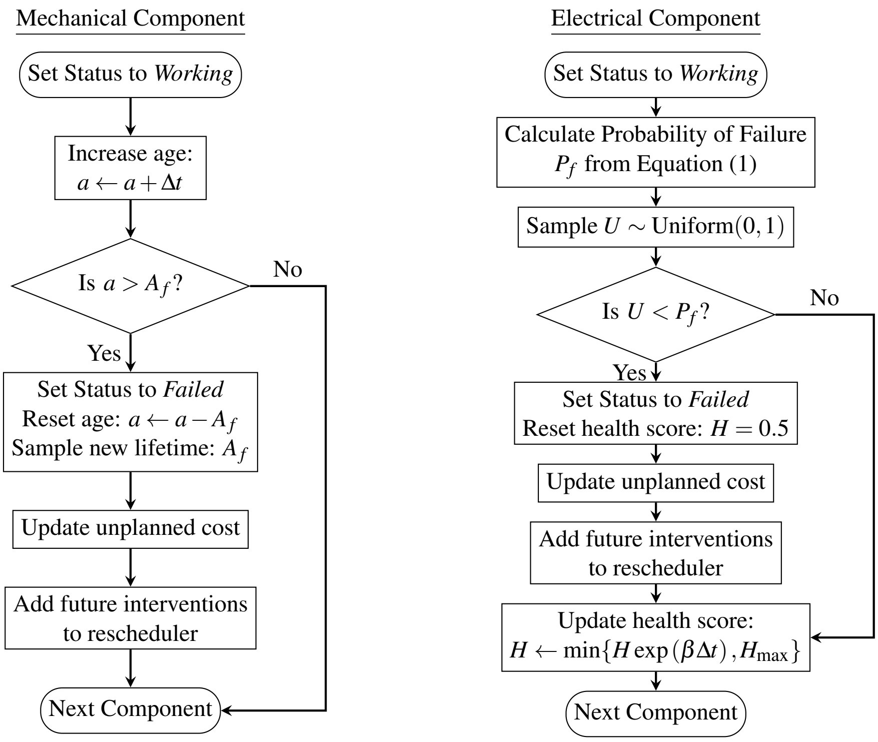

Figure 2: Update procedure for the two types of component. Here Δt is the time-step of the model.

The mechanism behind the failure of each component depends on its type. For some components, their lifetimes can be easily modelled using a time-to-failure distribution (such as a Weibull or Log-Normal distribution), in which case we partially utilise Discrete-Event Simulation ideas, mirroring the approach of Chiacchio et al. (2020). Given the current age of the component, A_0, we sample a failure age A_f from the lifetime distribution (conditional on being greater than A_0). At each time-step, the age is updated, and if it exceeds A_f, the component fails. For other components, where the probability of failure is often linked to a condition or health score, this approach is not possible. For example, the U.K. industry standard for electrical components used in power transmission is the CNAIM framework (Booth et al. 2017), which models the annual probability of failure as:

$$\Pr\{\text{Failure in next year}|H\} = K\left(1 + C\max\{H,4\} + \frac{C^2}{2!}(\max\{H,4\})^2 + \frac{C^3}{3!}(\max\{H,4\})^3\right) \tag{1}$$

where K and C are component-dependent constants and H is the current health score of the component expressed as a function of the component's age a:

$$H(a) = \min\{H_0 \exp(\beta a), H_{\max}\}, \tag{2}$$

with $H_0 = 0.5$, $H_{\max} = 10$ and β a component dependent ageing rate. Thus, components following the CNAIM framework will fail in the current time-step with the probability given in equation (1). Using a discrete-time model enables both types of component to be modelled in the same simulation.

When a component fails it is replaced by a new component and, if necessary, a new failure age A_f is generated. Once all components have been updated, the simulation uses the Reliability Block Diagram to check the status of the asset. A significant assumption of the time-step approach is that all failures are assumed to be concurrent. This can be mitigated with smaller step-sizes, but as it is assumed maintenance must be completed within a time-step, there is a lower limit on the time-step.

The key decision input to the simulation model is the maintenance intervention schedule. This describes when each intervention will be performed, and which components are affected by the intervention. An intervention will reduce the age or health score of each of the components it impacts. We do not assume the intervention is perfect. After the intervention, a new failure-age is then generated (if required). As a simplification, we perform interventions before the ages and health condition of components are updated. This effectively assumes that all the interventions take place at the beginning of the time-step, rather than distributed through the time window.

An important element in the simulation model is that components do fail. In this case, the future planned interventions for that component must be rescheduled. In reality, a new maintenance plan would be developed each year using the optimisation model. As this can take hours to run, it is impractical to achieve within each replication of the simulation model. Thus, we allow a user-specified heuristic rule for rescheduling interventions. We describe the default heuristic here. Suppose that a component failed during a year. At the end of that year, any future planned interventions will be moved to a year after which all impacted components have exceeded their specified age or health score threshold.

3.2 Model Outputs

The simulation model outputs a data set stating the cumulative costs incurred over the planning horizon and whether each component, Level 1 item or the asset failed during each time-step. Thus, by performing many replications, the simulation can be used to estimate the time-dependent reliability of the asset, Level 1 items and components (as measured by the probability of failure), as well as quantifying the uncertainty of the future total cost.

The total cost of maintenance over the time horizon is the sum of the planned intervention costs, the costs due to component failures and repairs, the disruption cost of downtime should the whole asset fail and the cost of lost usable life due to early replacement. A key advantage of using the simulation model in addition to the optimisation model is that we can analyse various possible future costs rather than simply a single prediction, enabling percentiles and prediction intervals to be generated.

Whilst the reliability of the asset is important, we can also look at availability of Level 1 items. This is defined as the number of a particular type of Level 1 item operating in each time-step. If these items work in parallel, a few failures may not lead to asset level disruption, and thus the optimisation model may not penalise this. However, it may impact the levels of productivity that can be achieved. This information is much harder to quantify from the optimisation model output, but can be naturally quantified by running the simulation many times and looking at the detailed output.

4 SENSITIVITY ANALYSIS

One of the points made in the literature review by de Jonge and Scarf (2020) is that relatively little work in the field of maintenance optimisation accounts for uncertainty in the lifetime distributions of components. Getting reliable data on the lifetime distributions is often difficult. For this reason, the CHARM tool allows engineering judgement to be used when fitting distributions. The consequence of this is that uncertainty in the parameter estimates cannot be quantified, making it very important to study the sensitivity of the performance to errors in the lifetime distribution estimates, as well as other parameters such as the cost of failure and the downtime caused by a failure.

As a system can involve hundreds of components, a full sensitivity analysis could be very computationally expensive. For this reason, we took a factor screening approach, aiming to identify the most influential input parameters on the overall cost. The value of this is that if the proposed maintenance schedule is found to be particularly sensitive to certain parameters, the optimisation could be re-run using conservative estimates for only those particular parameters, rather than considering the worst case in all parameters (which could be very conservative).

We applied Improved Controlled Sequential Bifurcation (CSB-X), proposed by Wan et al. (2010). The key idea behind CSB-X is that, if the sign of the effect is known (if it increases or decreases the total cost), parameters can be grouped and then screened together. If the total effect of the group is unimportant, each parameter in the group can be declared unimportant. Otherwise, the group can be divided in two, and each tested again. This greatly reduces the amount of time required to perform the factor screening, and CSB-X does this in such as way as to control the misclassification error rate.

In our application, many of the input parameters have an intuitive sign. For example, increasing the cost of failure is likely to increase the overall cost, and increasing the scale parameter of a Weibull lifetime distribution will make failure before an intervention less likely, decreasing the total cost. For these parameters, CSB-X can be highly effective. The speed of CSB-X depends on how well the factors are ordered; if all the unimportant parameters are grouped together, it is much easier to screen them out. But if this was known beforehand, it would be unnecessary to perform the screening. To help, we first run the simulation 1000 times and split the total maintenance costs across the components. We then list parameters in order of decreasing cost contribution of the associated component. This heuristic appears to speed up the approach considerably.

The impact of increasing the shape parameter of lifetime distributions is much more difficult to determine. So CSB-X could not be used for this purpose. An alternative that does not require the sign of the effect to be known is the hybrid methodology proposed by Shen et al. (2010), which includes CSB-X. We did implement this method but found that it came with a considerable computational cost.

5 APPLICATION

The asset system at hand is a Waste Management (WM) system of an industrial complex, which follows the structure outlined in Section 3. The overall structure of the WM system is shown in Figure 3. The Level 0 WM system is broken down into four Level 1 asset systems, which are connected in series. On the top of the diagram, there is one Mobile Cleaning System (MCS), while instances of Portable Tank Systems (PTS) and Static Cleaning Systems (SCS) are in parallel with each other and instances of Super Portable Tank Systems (SPTS) are in series. The MCS item consists of 24 components, the PTS items consist of 27 components, whilst both SCS and SPTS items are made up of 19 components each. The individual Level 1 items are given a label, e.g. SCS 34 refers to the fourth SCS item. All Level 2 components of the four Level 1 asset systems discussed are in Series with each other. It should be noted that Figure 3 depicts assets of Levels 0 and 1, however the same idea generalises for deeper Levels. This WM asset system, being used in an industrial complex is quite a complicated hierarchical structure with 476 individual components being aggregated into their respective parents, something that outlines the computational cost of the problem at hand, as well as the scalability of the model created.

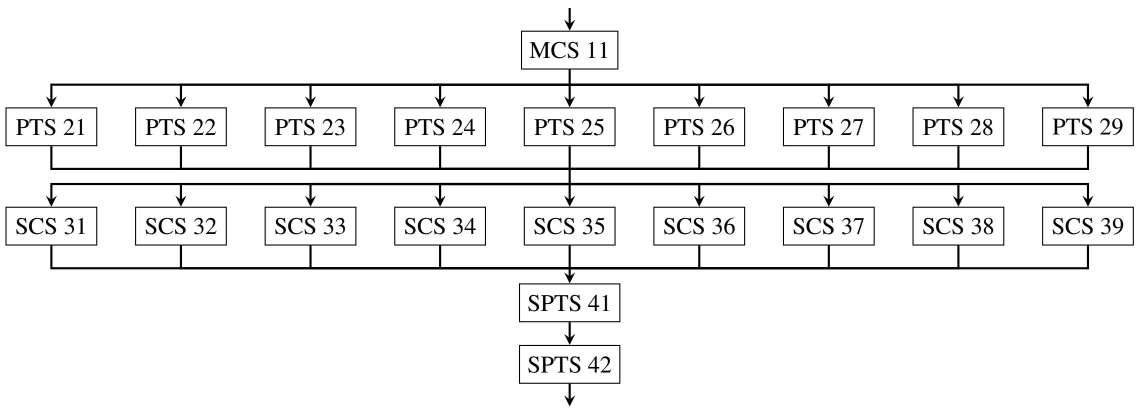

Figure 3: A Reliability Block Diagram of the Waste Management hierarchy.

The CHARM tool was used to model the time to failure for all components and then to optimise a maintenance schedule between 2021 and 2031, accounting for budget constraints for each year. The simulation used the same input data as the optimisation model as well as the resulting maintenance plan to estimate the cost distribution, the reliability of the system and the availability of Level 1 items. The results presented are based on 10,000 replications of the simulation with a time-step of 6 months. All cost units are scaled to be between 0 and 1.

The annual total and unplanned maintenance costs are shown in Figure 4. Whilst the highest annual costs are incurred upfront through a lot of planned maintenance, the variance in the costs increases considerably over time, caused largely by increases in the unplanned costs due to component failures. The maintenance plan reduces failure costs in the first half of the period, but is less effective later on.

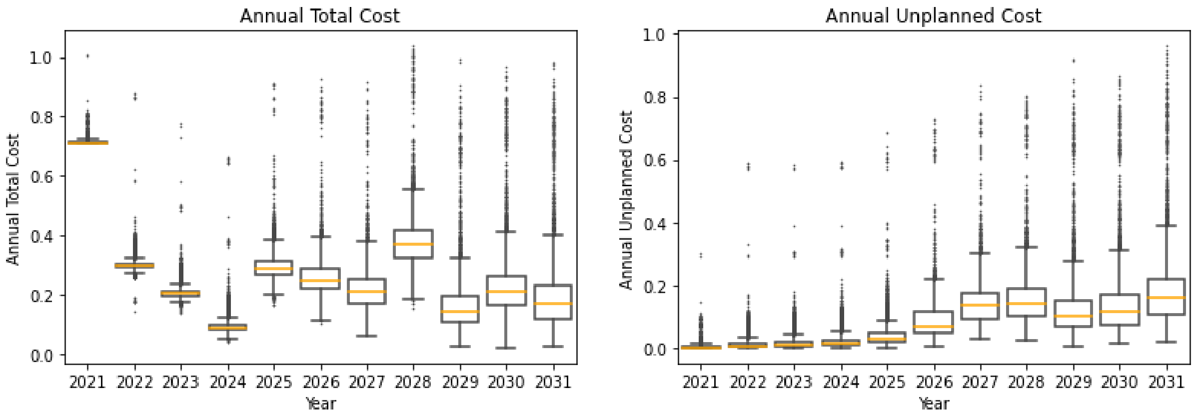

Figure 4: Box plots of the annual total and unplanned costs over the time horizon.

The stacked area plots in Figure 5 demonstrates how the annual costs breakdown into both cost types and Level 1 item groups. This can be done by different percentiles of the cost distribution, Figure 4 shows the 50th and 95th percentiles. Unsurprisingly, the planned costs remain fairly constant and it is the unplanned maintenance costs that dominate the latter years in the higher percentile case, with the PTS and SCS groups contributing significantly.

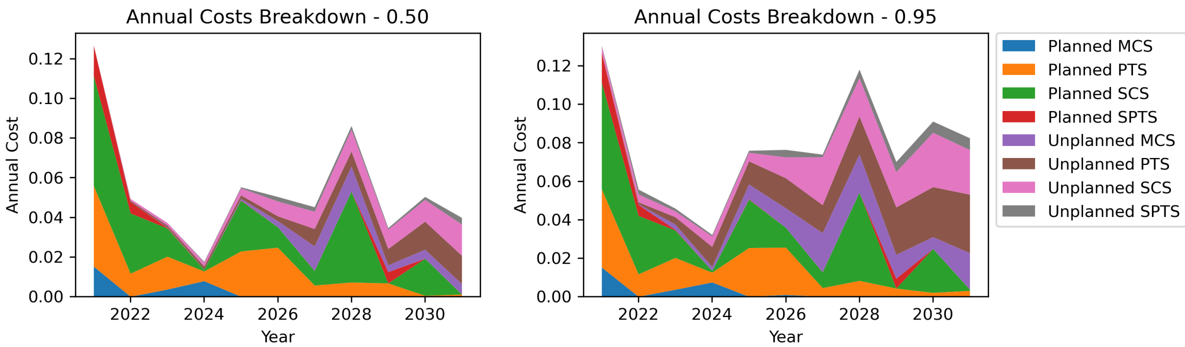

Figure 5: How the costs breakdown at different stages of the cost distribution.

The simulation is able to estimate the availability of groups of items over time. Whilst the PTS and SCS groups act in parallel (and are modelled as such in the optimisation model), lower availability leads to lower productivity. Hence, there are targets for the availability; seven PTS items and six SCS items are required to be available in each time period. Figure 6 indicates the probability of meeting these targets (green), having at least half of the target (amber) or falling below that (red). These plots highlighted a significant issue that is not obvious from the output of the optimisation model: that as time goes on the number of PTS items often fails to meet the target of 7. This indicates that PTS items need to be maintained more often, so that failures are reduced and we are able to meet the target.

Analysing the data further, Figure 7 demonstrates the cumulative probability of failure for seven items for PTS 21 (the other eight PTS items have similar plots). For several components, such as the panel hose and electrical supply, the cumulative probability of failure climbs very quickly between 2026 and 2030. This sort of result from the simulation model could then be used to feedback information into the optimisation model, as we could potentially change the maintenance thresholds of these components

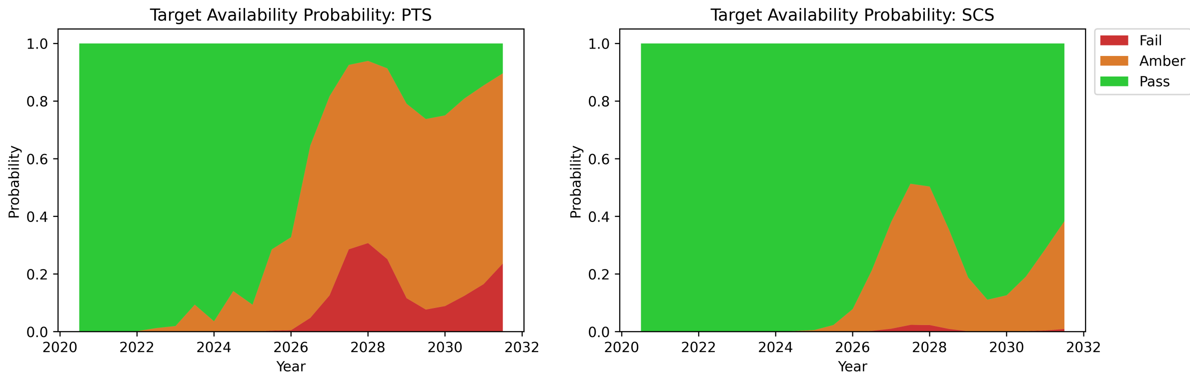

Figure 6: The probability of meeting the target availability for the PTS and SCS groups over the time horizon.

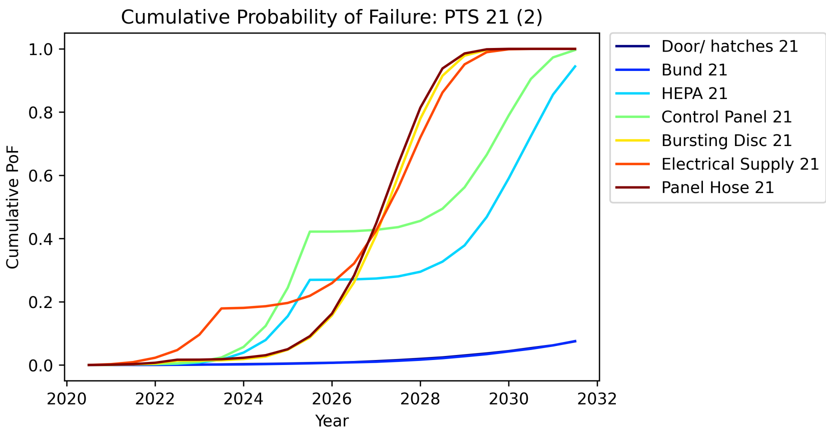

Figure 7: Cumulative probability of failure for the most vulnerable components of PTS 21.

to be more conservative. The likely consequence would be a greater prioritisation for these components in selecting maintenance and thus an improvement in the reliability of the Level 1 PTS group, which is going to drive down the unplanned costs of the asset type discussed earlier.

5.1 Application of Sensitivity Analysis

We applied the CSB-X screening procedure to the scale, cost and disrupted days parameters for each component type and the initial condition parameter of each individual component (constituting a total of 743 parameters). The aim here is to draw out parameters that have the largest influence on the expected total cost. This will allow us to see which parameters have the greatest requirement for additional data.

The thresholds for defining important and critical factors were 0.1% and 0.2% of the mean total cost, respectively. The experimental regions for scale parameters had problem specific definitions, whilst the others were varied by plus or minus 10%.

Despite the very large number of factors, we were able to identify the most influential input parameters within 30 minutes using 2 processors on a laptop and controlling the error rate at 5%. On average, the heuristic mentioned in Section 4 reduced the computational cost by over 30% (based on 50 replications of each procedure). This demonstrates the utility of CSB-X for sensitivity analysis when there are many input parameters. Ten input factors were identified, relating to eight component types. The most influential parameters were the cost and scale parameters for the bund component of the MCS and the flexible pipework of the SCS.

6 CONCLUSION

This paper has presented a discrete-time simulation model for improving the understanding of the stochastic nature of future maintenance costs and reliability of complex systems of assets under a particular optimised maintenance schedule. The simulation model is flexible and able to adapt to many systems based on the input data provided. The discrete-time nature gives the model the ability to model failure processes that are more easily modelled in either continuous or discrete time.

The results from our application demonstrate the advantages of using a simulation model alongside an optimisation model. As well as giving a clearer picture of the cost distribution and risk associated with any proposed maintenance plan, the simulation is able to highlight problematic behaviour of the optimised maintenance schedule, particularly the fact that several items that function in parallel can fail at the same time.

In further work, we anticipate that this framework will be able to form a feedback loop with the optimisation to improve solutions. The optimisation model is based on certain age or health thresholds that determine a desired window for maintenance. If the simulation model highlights undesirable behaviour, such as low availability of Level 1 items reducing productivity in certain periods, the detailed simulation output could help identify which of these thresholds should be made more conservative (i.e. shifting the window earlier) to improve the solutions the optimisation model generates.

We could also develop a more direct usage of simulation within the optimisation procedure. The applications of simulation optimisation within the maintenance optimisation literature are limited to either exhaustive grid searches (Barata et al. 2002) or low dimensional search problems (Zahedi-Hosseini et al. 2017). As large complex systems with budget constraints create high dimensional combinatorial optimisation problems, many of the cutting-edge simulation optimisation algorithms may not perform well. This could further motivate a multi-fidelity modelling approach to the optimisation.

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AUTHOR BIOGRAPHIES

LUKE A. RHODES-LEADER completed his PhD in Statistics and Operational Research at Lancaster University, where he is now a Lecturer in Management Science. His research interests are in analysis of simulation models, and their use alongside other modelling paradigms.

DAVID J. WORTHINGTON is a senior lecturer in Operational Research in the Department of Management Science in Lancaster University Management School. He researches the modelling and management of time-dependent queueing systems, and applications of Management Science in health-care. These research interests often coincide.

IAN GRIFFITHS is the Chief Technology Officer of Decision Lab where he oversees technical delivery within the business and its strategic development. He has a career in science and technology spanning 25 years and multiple sectors, including defence and security, water and infrastructure.

PANAGIOTIS SAMARTZIS is a Senior Consultant in Decision Lab, having completed his MSc studies in Operational Research at Lancaster University. He is an expert in Optimisation, Mathematical Modelling and Deep Learning, which he practices in a variety of sectors such as water, aerospace and asset management.